BIT ERROR RATE REDUCTION FOR WIRELESS COMMUNICATION SYSTEM USING ADAPTIVE CHANNEL EQUALIZATION

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DOCTOR OF PHILOSOPHY

By

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1. Introduction

The transmission of higher data rate and capacity to resist frequency selective fading and orthogonal frequency division multiplexing (OFDM) is a promising method in the current broadband wireless communications system. OFDM is used to divide a high-rate data stream into a number of minimum-rate flows transmitted simultaneously over a number of sub-carriers. In this system, the individual spectrum of the sub carrier with reduced frequency spacing is designed in a way that orthogonality of subcarriers with one another is maintained. It's a case of multi-wave modulation, consisting of closely spaced modulated carriers. The sidebands spread on either side when any kind of modulation like voice, data is applied. The receiver should be capable to receive the total signal and it must be capable of demodulating the same data. When the signal is transmitted and it must be separated by a frequency and be inserted by a guard band so that it can be separated by a filter easily. This case is not applicable to OFDM. As the sideband of each carrier overlap, there is an expectation of receiving the signal without any interference.

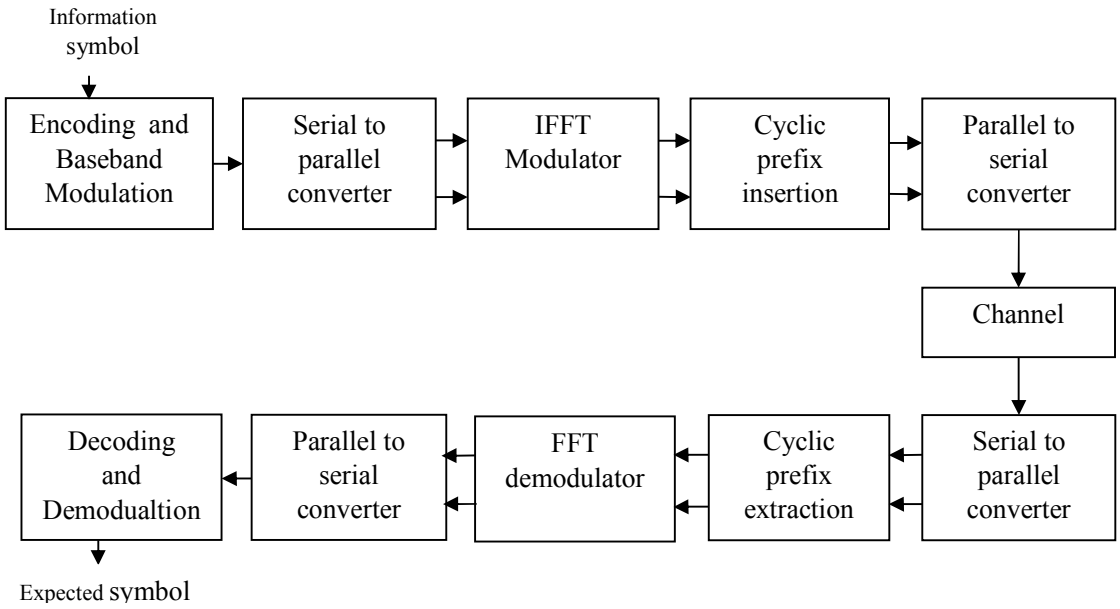


Figure 1. Diagram of OFDM

It is achievable a carrier spacing as reciprocal to symbol period [1]. The input bit data stream is modulated as baseband shown in figure1, feeding a modulation scheme. Variety of modulation schemes are engaged as BPSK, QPSK and QAM with signal constellations of a different type. TheOFDMs another typeis where distinct modulation is done on each subchannel. In this encoded data in a frame where the baseband signal is modulated in a serial form known as DFT frame or interframe where the modulation takes place on every

parallel substreamof symbols of adjacent DFT frames. In N different sub-streams data symbols are paralyzed. A separate carrier is modulated through IFFT modulation block through each stream. The ISI is vanished by insertion of the cyclic prefix. Cyclic prefix L is anaddition of the modulated IFFT symbol computed by utilizing the copy mechanism for the last samplesL symbol in front. Converteddata as back-serial, OFDM symbol is formed which modulates a carrier of higher frequency prior to transmission to the channel. Inverse operations are performed on receiver side: the data is transformed to a baseband signal and discarding of cyclic prefix. The FFT demodulator ideally recovers the same form of transmitted symbols. The converteddata serially andeffective demodulation scheme is to analyze the symbol which is transmitted. The features of OFDM are:

- Allow overlapping, efficient use of spectrum.
- Solve Multipath and ISI problem.
- Computationally Efficient.
- Supports various multiple access schemes.

There are some constraints of OFDM given below:

- Extreme peak to average power ratio: This signal has the great dynamic range and has an amplitude variation such as noise. The amplifier linearity is necessary and can be capable of handling great variations of amplitude and efficiency RF amplifier is affected and it cannot operate at a higher level of efficiency.
- It is sensitive to drift as well as frequency offset which is a disadvantage of OFDM. Single carrier systems are less sensitive.
- High synchronism accuracy.
- The large dynamic range is needed by receiver amplifiers of low noise.
- The guard interval causes bandwidth and power loss.
- Multipath propagation must not be present in orthogonality has an unaffected dependency.

The higher data rate wireless communication has drastically expandedover the last decade. Conventional carrier system is a way to transmit high data rate. Since the transmission bandwidth is greater in comparison with the coherence of the channel, equalizers of high complexityare required at the receiver for recovery of accuratetransmittedinformation. A multicarrier technique solves the problem. Mostdescription of the input signal, noise introduced or the dynamics of the physical system change with time [1, 2]. Therefore a requirementfor digital filters whoadapts to these changes so that the desired output is

achieved. This is achieved by varying coefficient of the filter in response to the various changes. Filters with changing coefficients are called Adaptive Filter. One of the major applications of adaptive signal processing is channel equalization. In a perfect communication channel, the received information is identical to that of transmitted. The transmitted data could be inferred by a channel with three types of distortion effects: power degradation, multipath time dispersions,and thermal noise. The way of recovering a data sequence from corrupted channel samples is known as channel equalization [3]. The baseband transmission along with a channel equalizer is presented in Figure 2. The channel represents the combined response of the transmitter filter, the actual channel, the receiver filter. The additive noise arises from thermal noise in electronics circuits and possible cross-talks from neighboring channels.

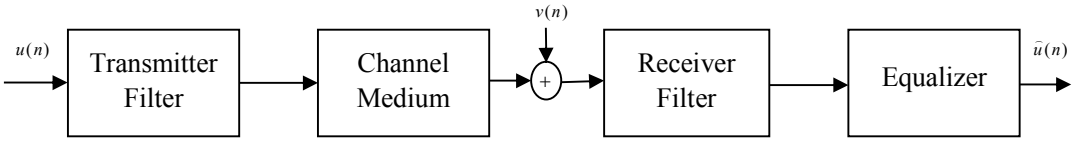


Figure 2. Baseband Transmission System

Here the transmission system has components or elements: the transmitter filter, the actual channel, the receiver filter. The additive noise denoted by $v(n)$arises from thermal noise in electronics circuits and possible cross talks from neighboring channels. The data transmitted appears in the type of amplitude pulses, are distorted by the channel. The most significant among the different distortions is the pulse spreading effect, which occur due to dissimilar impulse response with ideal impulse response function. This distortion result in the interference of the neighboring data symbol with one another, thereby making the detection process through a threshold detector unreliable. The phenomenon of interference between neighboring data symbols is known as *Intersymbol Interference* (ISI). The channel introduces distortion while reducing the impact of additive noise levels at the threshold detector input as much as possible.

1.2 Motivation

The advancement of internet techniques, the possibility of high-speed data communication techniques via the channelis a challengeable issue in the communication field. Also, there is a needfor high-speed communication in the existing channel. Basically, the channel to transmit the data at higher rate distorts the signals causing ISI effect. Numerous signal processing techniques are applied at receiver section to overcome these problems. Channel equalization widely employs ina digital communication system and is made adaptive to changes made by

channel. In numerous applications related to adaptive equalization, convergenceby adaptive equalizer is necessary. Compensating for time-spread introduced by the channel by using adaptive equalization, making it possible to efficiently transmit bandwidth over the telephone and radio channels. Equalizers are used as compensators for channel-induced distortion. In most digital communication systems, the channel characteristics may not be known apriori. In such cases, the transmission with receiving filters is designed assuming a distortionless channel and then using an equalizer to lookto channel distortion [5].

2. Research Objectives

The following are the major objectives of this research study:

- To equalize the fading effects of a communications channel on the signal using thenumerous types of equalizers and to implement adaptive algorithms for channel equalization.
- To determine the tracking behavior and compute BER by transmitting and receiving a predetermined bits under different SNR scenario.
- To compare the different types of equalizers based on their bit error rate.

3. Problem Statement

The main aim of the communicationmethod is to transmit information from one end to another end without any distortion via any channel (sky bound, earthbound etc.). When the information goes through the channel from the transmitter to the receiver, the channel is affected by noise and ISI. This results in changes in the characteristics of information and we get corrupted information at the receiving end.

In digital communication, data is transmitted pulse form. This creates a bandwidth problem and ISI effects. Therefore equalizers are required to remove or reduce these problems [6,7].

4. Literature Survey

The transmission of information with ISI additive noise has recently gained considerable attention. The mitigation of these effects is the task of the equalization filter. Intensive studies have been done to handle this problem. Transversal filters are used for the distortion and noise drawbacks of digital comm. A system based on equalizer is discussed [5]. The state-variable formulation has been employed in designing receivers for band limited data-transmission systems [6,7], which takes a class of linear-modulation data-transmission systems. Equalizer for use in the new Data Set 203 is discussed in [8] to achieve minimum cost and size while maintaining precision operation which results in a reduction in size and cost over the equalizer implemented with the semi-digital approach using integrated circuits

and thin film resistor ladder networks. An exploratory study has employed discrete Kalman filter as an adaptive equalizer for the stationary case, though the Kalman filter is applicable to the time-varying case is described in [9]. A utilization of decision feedback to mechanize the adaptive nonlinear modified Kalman Equalizer (KE) is proposed in [10], with the initial state variable estimated by a prediction process. In case of the mobile communication environment, three equalizer structures were studied [11,12] and it was found that the MSE of Adaptive Kalman Decision Feedback equalizer (AKDFE) is better in case of High Frequency (HF). To reduce the MSE a solution has been found in [13] with Infinite Impulse Response (IIR) which provides good results for MSE but complexity increases. Then Channel Estimator Equalizer (CEE) and Adaptive Kalman Equalizer (AKE) are compared by gradient algorithm [14], AKE is more efficient but sensitive to the accuracy of channel estimation. A novel scheme in which Direct equalizer (DE) and Equalizer Channel Identifier (ECI) has been proposed [15] in which adaptive IIR equalizer is dealing with minimum phase channel which achieves better convergence speed and MSE. In the case of a wireless channel, traditional equalization schemes based on channel selection and equal routing cannot track channel changes, because they require some training codes to adapt the equivalent. Input Multiple Output Decision Feedback Equalizer is a MIMODFE that is able to identify, track and equalize the time-varying channels that use the KF filter to ensure a good result [16]. For non-stationary channel identification, algorithm dependency on Kalman channel identification is used. The unknown state estimated is a straight sequence of sending signals containing Network of Kalman Filter as NKF. The network is dependent on the modeling of posterior symbol state probability density function found by weighting the Gaussian Sum.The performance of BER of the NKF equalizer is seen to have improved [17]. The latest approach for the real-timeconsideration of the AKE is proposed in [18] with two Kalman filter which runs to perform detection and estimation. The structure of the parallel structure is used to update the time and measurement equations. The performance of Parallel Pipelined Kalman Equalizer (PPKE) is better in comparison to the Kalman-Least Mean Square (K-LMS) and Kalman-Recursive Least Square (K-RLS).Now the association of LMS, as well as RLS in terms of BER performance, is carried out with different adaptive algorithms in [36]. BER of MMSE equalizer-based receiver is on the lower side as compared to Zero Forcing Equalizer in [41]. Different filters used and perform better as compared and a characterization of the minimum network resource for the SNR required stabilizing the networked control system over the fading channel[38].

Research Gap

Equalization and detection are marked as a classification problem. Digital data sequences of received observations can be partitioned using the different adaptive algorithms. The advantages of the system are its simplicity, thereby reducingcomputational complexity compared to other equalizers. Experimental results and comparison with different algorithms can be done.From the comparative study of results, performance can be analyzed with other equalizers and adaptive algorithms in terms of convergence.

5. Adaptive Channel Equalizer

The groundsfor adaptive channel equalization are forbalancingthe distorted signal in a channel. Communication systems transmit point-to-point signals via a communication channel, such as an electric cord, fiber optic cable, or wireless radio link. During the transmission process, the signal that contains information might become distorted. To compensate for this distortion, you can apply an adaptive filter to the channel as shown below.

Transversal filter is a base for implementation of an equalizer. Initially,the equalizeris trained that needs acquaintance of the transmitted symbols since they should be used as the wanted signal samples for adaptation of the equalizer tap weights. This follows from the fact that the equalizer output should ideally be identical as the transmitted data symbols. We, therefore, require a configuration period during which the sender sends a series of training codes to the receiver. This is called training mode. Inthe end, this mode taps weights of an equalizer convergence close to the optimal values. The detected symbols would then be similar to the transmitted symbols with probability close to one. The detected code can then be treated as a desirable signal for further adaptation to the equivalent so that potential changes in the channel can be tracked. This is known as decision making. The decision directed mode works long as the channel variation is slow enough so that the adaptation algorithm is able to follow the channel variations [8,9].

5.1 Kalman Equalizer for State Estimation

The system shown in Figure 3 is for a time-invariant channel whose coefficients are known. But in practical cases, most of the channel istime-varying. So to implement them in the above scheme first we have to estimate the channel coefficients [10,11,12]. To estimate the channel coefficients we use adaptive filters [13,14]. The RLS and LMS adaptive filter for channel estimation are explained above. The Adaptive Kalman equalizer integrated with channel identification is shown in Figure 3.

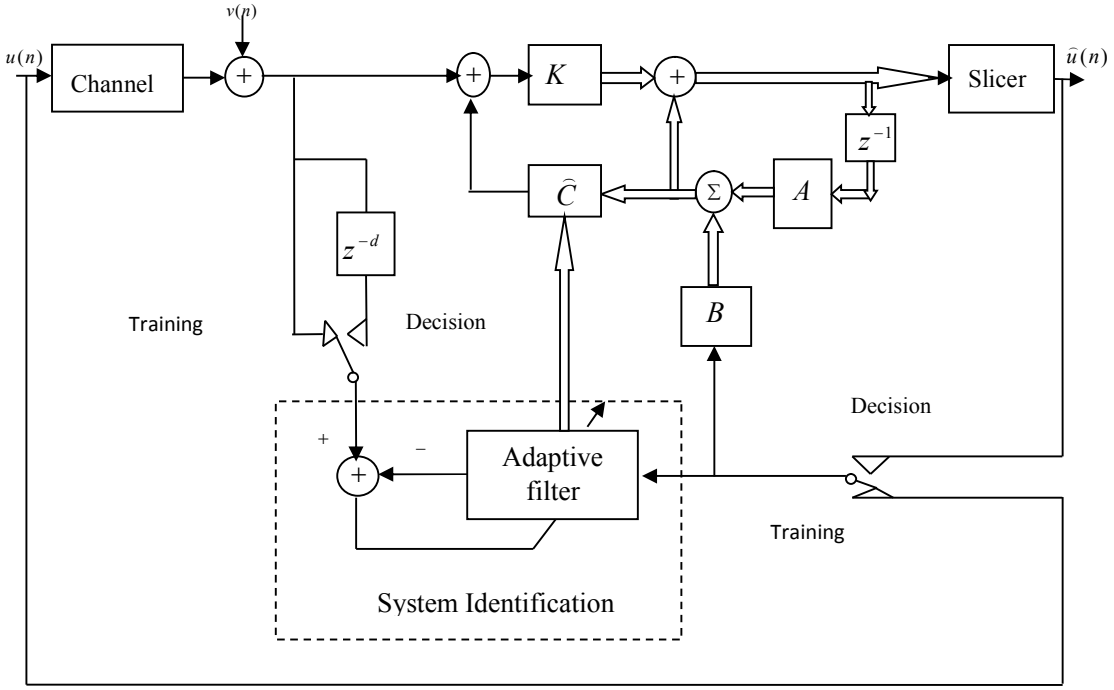


Figure 3. Channel Equalization for Non-Stationary Channel

To estimate the channel we need input sequence at the receiving end. So the system is operating in two modes i.e. training and decision directed mode. In training mode, we provide a finite training sequence as input which is also known at receiving end. The system parameters are compensated in training mode. The system mainly operates in direct mode when actual transmission and receiving information takes place. In the decision _directed mode the output of slicer i.e. the estimated input $\hat{u}(n)$ at the receiver is used as input for the adaptive filter.

We are already using $u(n)$ and $\hat{u}(n)$ as input to adaptive filter for training and decision directed mode respectively at receiving end, the same input can be provided to Kalman filter i.e. decision directed mode $\hat{u}(n) = \text{slicer output}$ whereas in training mode $\hat{u}(n) = u(n)$. This accomplishes input rather than using mean value for the actual signal. The algorithms for Kalman channel equalizer with Least Mean Square as LMSplusRecursive Least Square as RLS are given in subsequent sections [15,16].

6. Scope of Work

6.1 Extended Kalman Filter

The Kalman filter identifies thetrouble of trying to evaluate the state of a process that is controlled separately and linear random difference equation governs it. The Kalman linear

filter is known as the current mean with variance as the extended Kalman filter (EKF). Using the Taylor series, one can derive the estimate of the present estimate employing partial derivatives for process and the measurement functions to calculate the estimates even in nonlinear relationships face. The assumption of that the process has a state vector, but now the criteriaare examined by the non-linearstochastic difference equation

$$\hat{x}_k^- = f(\hat{x}_{k-1}, u_k, w_k) \quad (1)$$

By the measurement $$z_k = h(x_k, v_k) \quad (2)$$

The variables $w_k$and v_k are the process plus measurement noise. The case has the non-linearfunction f in equation ththe at identifies the state at the prior time step $k-1$ to the state at the current time step. It includes the parameters with driving functithe on $u_k$plusthe zero-mean process noisew_k. $h$function in the evaluative equation is a non linear function that correlates the state to the measurementz_k.The two random variables values is not known then one can approximate the state plus measurement vector as

$$\tilde{x}_k = f(\hat{x}_{k-1}, u_k, 0) \quad (3)$$

$$\tilde{z}_k = h(\tilde{x}_k, 0) \quad (4)$$

$\tilde{x}_k$ is aposterioriestimate of the state.

The estimation of a process with difference and measurement as non-linear, again equations are consideredwhich linearizeestimate of equation (1) and (2)

$$x_k \sim \tilde{x}_k + A(x_{k-1} - \tilde{x}_{k-1}) + Ww_{k-1} \quad (5)$$

$$z_k \sim \tilde{z}_k + H(x_k - \tilde{x}_k) + Vv_k \quad (6)$$

$x_k z_k$= actual vectors as state and measurement.

$\tilde{x}_k$,$\tilde{z}_k$=approximate state and measurement.

$\tilde{x}_k$= aposteriori estimate of the state at step$k$,

A, WH, VEmploys Jacobin matrix of partial derivatives of x, w, x, v. Prediction and measurement errors are

$$\tilde{e}_{k1} \sim A(x_{k-1} - \hat{x}_{k-1}) + \varepsilon_k \quad (7)$$

$$\tilde{e}_{k2} \sim H\tilde{e}_{k1} + \eta_k \quad (8)$$

ε_k and η_k represents independent random variables with zero mean and covariance metrics$WQW^T$and VRV^T with $Q$and R. Equation (5) and (6) are linear and identifies the difference and measurement equation from Discrete Kalman Filter. The estimates help us to obtain posteriori estimates for non linear process as

$$\hat{x}_k = \tilde{x}_k + \hat{e}_k \quad (9)$$

Predicted value of $\hat{e}_k$= zero, the Kalman Filter equation estimates$\hat{e}_k$ is

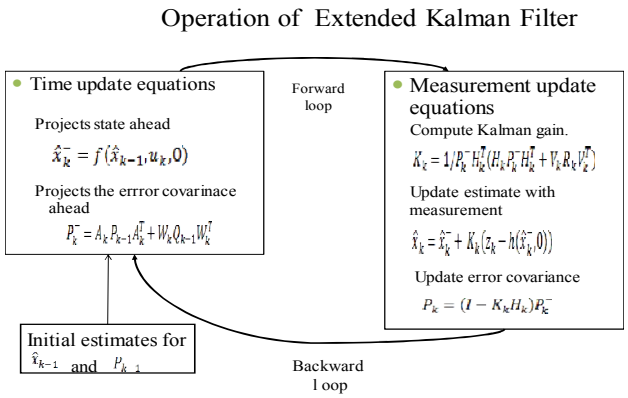
$$\hat{e}_k = K_k \tilde{e}_{k2} \tag{10}$$

Putting equation (7) in (8)

$$\hat{x}_k = \tilde{x}_k + K_k \tilde{e}_{k2}$$

$$= \tilde{x}_k + K_k(z_k - \tilde{z}_k) \tag{11}$$

The necessary operation of the EKF is shown below containing time update equation and measurement equation



6.2. Adaptive Filter

It is a combination of filter structures whose parameters are updated by adaptive algorithms.

6.2.1. Filter Structure

The adaptive filter can be implemented in many different configurations or implementations. The choice of structure can affect the complexity of the criteria and the number of iterations necessary to the requiredlevel of performance. Essentially, there are two main types of adaptive digital filter applications that vary in pulse response, FIR and infinite pulse response (IIR). FIR is performed in non-recursive structures, while IIR filters are performed using recursion

6.2.2. Finite Impulse Response

The commonly used adaptive FIR filter is a transversal filter, also known as a tapped delay line that implements an all-zero transfer function with standard direct form implementation without feedback. For this implementation, the output signal is a combination of filter coefficients that produce a quadratic mean square error function with an optimal solution that is unique. In terms of computational complexity, convergence speed, and finite word length attributes, other alternative adaptive FIR implementations are also used to achieve improvements over the transversal filter structure.

6.2.3. Infinite Impulse Response

The implementation of large-scale IIR filters isthe implementation of the direct model of the channel due to simple implementation and analysis.To resolve the problem of convergence and other issues, different applications are proposed to overcome the limits of the direct native structure. [21, 25].

6.3. Adaptive Algorithms

Adaptive algorithms are classified as adaptive algorithms based on the sample and cluster alignment [26,27]. In a sample-by-sample adaptive algorithm, adaptation can occur in both the time and frequency domains. The sample-by-sample adaptive algorithm will further generate two types of algorithms. One type of filter that includes sample-by-sample updates in the time domain is called a time-domain adaptive algorithm. These algorithms (LMS, RLS and its variants) are popular for their many advantages [25, 28, 29].

In the next section, we will briefly review the algorithm which is commonly used to update the filter in time domain sample-by-sample.

6.3.1 Recursive Least Square Algorithm(RLS)

RLS algorithm is dependent onthe reductionof the weighted squared error sum [26, 27]. In this RLS algorithm initialization, the inverse of the autocorrelation matrix and the option of forgetting factor are t. The appropriate initial value must be provided for the RLS algorithm. The need toforgetting considered and factors also affectthe behavior of convergence and tracking [21, 23]. RLS algorithm calculates calculation plus storage complexity. It'sappropriate to consider RLS algorithm because of high convergence speed. RLS algorithm is considered as adaptive filters to make the filter coefficients which concerns to recursively giving the least squares of signals having errors and difference of the desired and the actual one. In contrast to other algorithms designed to reduce the MSE. The difference is that the RLS filter relies on the signal itself, while the MSE filter relies on their statistics (specifically, the autocorrelation of the input and the cross-correlation of the input and the desired signal). If these statistics are known, an MSE filter with fixed coefficients can be constructed.

$$J = \sum_{i=0}^{N-1} \lambda^{n-i} e_i^2(n)$$

$$Q_n = \sum_{i=0}^{N-1} \lambda^{n-i} (xrls)_i (xrls)_i^T$$

$$r_n = \sum_{i-0}^{N-1} \lambda^{n-i} (xrls)_i d_i$$

$$\sigma_d^2(n) = \sum \lambda^{n-i} d_i^2$$

Now our cost function becomes,

$$J_w = \sigma_d^2(n) + 2r_n W^T + W^T Q_n W$$

and for this cost function, the optimum weights are calculated as,

$$W_{opt} = Q_n^{-1} r_n$$

For calculation of one single value of Q and r there are many calculations involved. So we find a change in these variables in terms of their last values and they come out to be,

$$Q_n = \lambda Q_{n-1} + (xrls)_n^T (xrls)_n$$
$$r_n = \lambda r_{n-1} + (drls)_n (xrls)_n$$

Again calculation of Q^{-1} is very time consuming and cumbersome job. So we use matrix inverse lemma to calculate it and define a new variable $Q_n^{-1} = (\Pr ls)_n$ and using matrix inverse lemma,

$$(\Pr ls)_n = \lambda^{-1} P(rls)_{n-1} - \frac{\lambda^{-1} (\Pr ls)_{n-1} (xrls)_n (xrls)_n^T (\Pr ls)_{n-1}}{\lambda^{-1} (xrls)_n (\Pr ls)_{n-1} (xrls)_n^T} \qquad (12)$$

and optimal is modifies as, $W_{opt} = (\Pr ls)_n r_n$

Putting this value of $(\Pr ls)_n$ and simplifying it will result as,

$$(wrls)_n = (wrls)_{n-1} + \frac{(\Pr ls)_{n-1} (xrls)_n (erls)_n}{\lambda + (xrls)_n (\Pr ls)_{n-1} (xrls)_n^T} \qquad (13)$$

This is the RLS algorithm where $(erls)_n$ is error signal with the value of weight vector $(wrls)_n^T$ defined as [26,28].

$$(erls)_n = (drls)_n - (wrls)_n^T (xrls)_n \qquad (14)$$

where λ is a forgetting factor, $(drls)_n$ is a desired signal of RLS, $(erls)_n$ is the error signal of RLS, $(xrls)_n$ is the input vector, $(wrls)_n$ is a weight vector of RLS, Q_n is anautocorrelation, r_n is a cross-correlation.

6.3.2 Least Mean Square Algorithm (LMS)

This algorithm is the most commonly used asan algorithm for adaptive filtering applications, the fact of simplicity plus low implementation cost. The algorithm is defined by the equations:

$$(elms)_n = (dlms)_n - (wlms)_n^T * (xlms)_n \quad (15)$$

$$(wlms)_n = (wlms)_{n-1} + \mu * (xlms)_n * (elms)_n \quad (16)$$

where μ is an adaptive step size parameter, $(elms)_n$ an error signal of LMS, $(dlms)_n$ desired signal of LMS, $(wlms)_n$ weight vector of LMS, $(xlms)_n$ input vector of LMS.If μ is large then algorithm not be convergent in a mean square algorithm. Sidewise, if μ is small then the convergence of the algorithm will be slow. It can be shown that the LMS algorithm is stable for $0 < \mu < \frac{2}{\lambda_{\max}}$ where $\lambda_{\max}$ is the largest_Eigen valueof matrix as input data.

The LMS algorithm is popular because of greatadvantages. However, it is noted that the convergence speed is slow when the LMS algorithm is used for adaptation, especially for longer filter lengths. In addition, adaptive filter convergence is slow due to step size constraints, depending on the characteristics by input signal [21, 23]. Some methods such as; therefore, pre-whitening of input signals and the like have been explored to improve the convergence speed of the LMS algorithm. These methods considered to better the convergence speed of the LMS algorithm, but amplify some complexity in computation.More common forms of LMS algorithm isNormalized LMS as NLMS[21,29], Proportionate NLMS (PNLMS), Affine Projection Algorithm (APA).

NLMS is defined as,

$$(enlms)_n = (dnlms)_n - (wnlms)_{n-1}^T (xnlms)_n$$

$$(wnlms)_n = (wnlms)_{n-1} + \frac{\mu}{\delta + \left\|(xnlms)_n\right\|^2} (xnlms)_n (enlms)_n$$

where $(enlms)_n$ error signal of NLMS, $(dnlms)_n$ desired signal of NLMS, $(wnlms)_n$ weight vector of NLMS, $(xnlms)_n$ input vector of NLMS, δ regularizing parameter. Stability and convergence properties for NLMS are considered by a step-size factor. The NLMS algorithm is stable; NLMS stability is independent properties of the input signal. In addition, NLMS offers faster convergence rates for associated and unrelated LMS data. Both LMS along with NLMS algorithms are efficient and have complexity in computation. Although the computational complexity of LMS and NLMS is the same, NLMS requires additional calculations to obtain regression or vector norms and further uses the normalization of adaptive step sizes [6, 29]. We won't discuss other LMS variants; instead, we will make some rough comments on their performances. But this method depends on the apriori knowledge concerning the current echo path impulse response and the ability to adjust the step size accordingly. The other variant APA isa generalization of the NLMS algorithm. But its computational complexity is more than NLMS algorithm [30,36].

6.3.3 Bit Error Rate

A generation of a long sequence of random bits takes place, which provides transmitter input. The transmitter formats the bits in a form of digitalized signals that will be transmitted via the analog channel. The channel is simulated by adding a quantity of noise to the transmitted signal. Then the noise signal becomes receivers input. The receiver disconnects the signal to produce a series of retrieved bits. Finally, comparison analysis of received bits with the sent bits and calculate the error. Calculate the bit error ratio (BER) as the sum of the bits of errors in the sum of bits in the sent signal.

$$BER = n_e / n \tag{17}$$

The ratioofan integer is plotted for different SNR values to study the performance of the equalizer. BER is usually depicted on a two-dimensional graph. A graph is created by a series of points on BER vs. SNR. The SNRis represented in decibels (dB)[33-36].

6.3.4 Cuckoo Search Optimization

Cuckoo Search (CS) is another heuristic meta-heuristic nature, in any application in almost no printing. In addition, and other existing meta-heuristic calculations (eg, PSO, GA) associated method is unique. Cuckoo Search is a populace for calculation as like Genetic Algorithm and Particle Swarm Optimization, however, the determination instrument is

distinctive and it is more like congruity inquiry. The randomization is more effective as the progression length is overwhelming followed and hence any huge stride is conceivable.

CS in the number of parameters are worse than GA and PSO and more, so it is more general and can be adjusted to a rationalization of the broader categories. CS can even reach the yuan bee calculations.

CS fulfills two essential attributes of present-day meta-heuristic calculation:

- Increase and,
- Expansion

Increase alludes to the way that the issue at first hunt down ebb and flow the best arrangement and after that at last hunts down worldwide arrangement. Expansion implies the calculation that investigates the inquiry space proficiently.

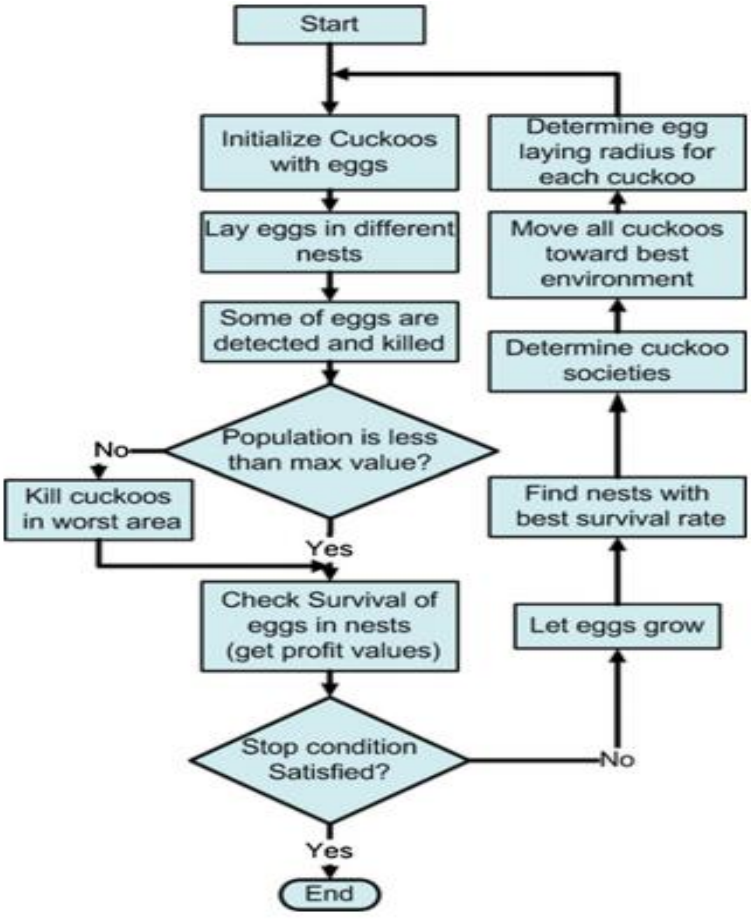


Figure 4. Cuckoo Search Optimization algorithm

CS (Cuckoo Search) is given by Yang and Deb is a nature enlivened calculation which depends on their forceful proliferation procedure that is few types of cuckoo lay eggs in another flying creature's home in a parasitic way. Three ways for the brood parasitism are as follows:

- Intra-particular brood parasitism.
- Helpful rearing
- Settle takeover.

A few animal types, for example, Ani and Guira cuckoos place their eggs into the shared homes, however, it might evacuate another’s' eggs to enhance incubating likelihood of their own eggs.

- In cuckoo seek three admired standards are formalized as takes after:
- Every cuckoo lays one egg at once and dumps its egg in haphazardly picked settle.
- The finest home with the elevated caliber of eggs persists the people to come.

The number of accessible hosts is changed and the eggs produced by the rhododendron are found by the host with the likelihood dad [0,1]. In this case the main building area construction area construction area construction area construction area construction area construction of the new home.

The part dad of n homes is supplanted by new homes. For a boost issue, the quality or wellness of an answer can basically be relative to the goal work. In light of the over three principles, a calculation named cuckoo hunt is given by Yang and Deb. This calculation appears as the flowchart in the figure given underneath.

- Fundamental strides required during the time spent Cuckoo inquiry are given underneath:
- Contrast the cuckoo's egg and the arrangement of accessible hosts.
- Haphazardness is added to it by utilizing Levy flight to pick have homes.

The above strides create an arrangement of value arrangements and an arrangement of disposed of arrangements.

In view of the Ranking capacity best arrangement is acquired from the arrangement of value arrangements while disposing of the most noticeably awful homes.

At the point when another arrangementis produced x(t+1) for, say, a cuckoo I, a Levy flight is calculated [4] as follows:

$Y_j^{((Q+1))}=Y_j^{((Q)) } +\alpha \oplus Lévy(\lambda)$

Where $\alpha > 0$, it is the progression estimate that ought to exist identified with the sizes of the issue thought about. Much of the time, we utilize $\alpha = 1$. The Levy flight basically gives an irregular walk as the arbitrary stride length is drawn utilizing Levy appropriation agreed by the condition is shown below:

$Lévy \sim v = q -\lambda , (1< \lambda \leq 3),$

It gives a vast change by a limitless mean. The means shape an arbitrary walk prepare by a power-law step-length circulation by a substantial tail. A portion of the novel arrangements are created by Levy walk adjacent to the best arrangement acquired as such, this velocityup to the neighborhood look. Nonetheless, some portion of the new arrangements is created by mulling over the randomization idea. In any case, whose areas ought to thoughtfully be sufficiently far from the present best arrangement, this guarantees the framework does not get caught in a nearby ideal.

6.3.5 ARTIFICIAL NEURAL NETWORK

Machine learning algorithms help in decision making, while ANN classifies decision making in groups. Artificial neural networks consist of simple elements that operate in parallel. Artificial neural networks basically work with weights. When an ANN initially presents a pattern, it randomly ‘guesses what it might be. Then it will see how far its answer is from the actual answer, and adjust the weight of the connection appropriately.

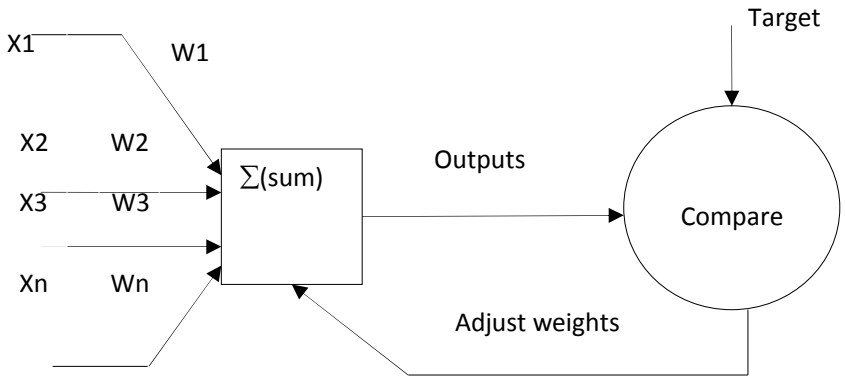


Figure 5. Artificial neural network

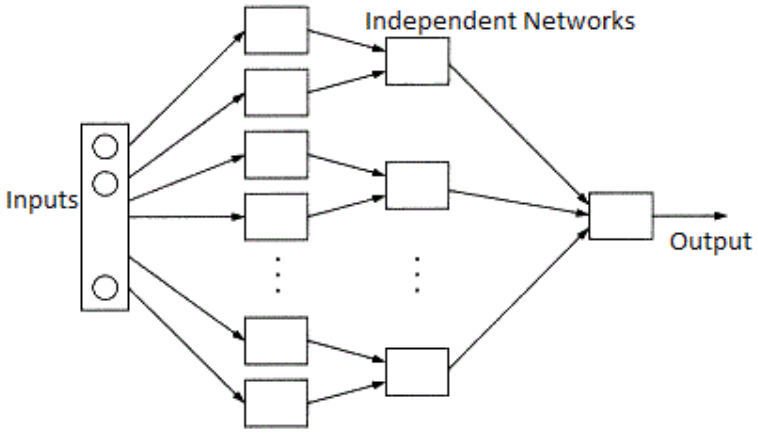


Figure 6. Structure of ANN

The above figure represents the three-layer structure input, independent layer,and output layer. The input nodes are represented by a circle, hidden layer nodes and output nodes are represented by a square box.

- **Activation function**

The ANN can be trained to perform specific functions by adjusting the values of the weights between the units. The artificial network function is determined by the connection between elements. This function is used to generate a related output based on the weighted sum of inputs. The output is compared to the target; if the generated output is compatible with the actual output, the input is correct, otherwise, the output will be adjusted based on weight.

- **Sigmoid function**

It is a real value and differentiable, with negative and positive first derivatives, a local minimum, and a local maximum. It produces an 'S' curve.

$$sig(a) = \frac{1}{1 + e^{-a}}$$

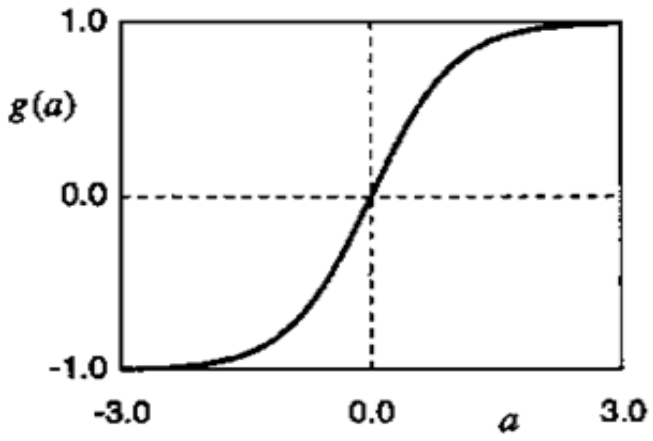


Figure 7. Sigmoid function

In the proposed research work, the sigmoid function is utilized as an activation function to generate output. It is used in ANN to add nonlinearities in the architecture. The ANN calculates a linear combination of its input (I/P) signals and a sigmoid function is applied to the output. It satisfies the characteristics among the derivative of the function and itself, so it becomes simple to compute. Its derivatives are utilized for learning scheme.

Training ANN

ANN's training requirements are based on certain learning processes. Using learning methods, the network is forced to produce specific responses to specific inputs. When the information about the input is unknown or incomplete, it becomes necessary.

i. Supervised learning

In this system, we assume that at each moment when the input is applied, the desired response of the system is obtained. It tries to predict the result of a known example. Such systems compare their predictions with known results and learn from mistakes.

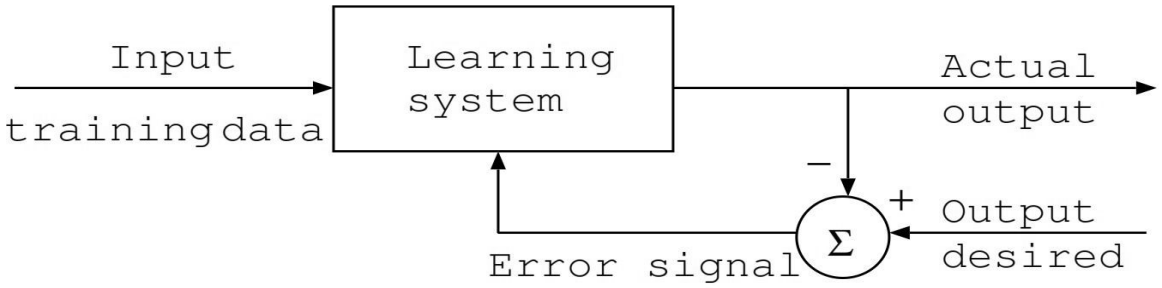


Figure 8. Supervised learning

In this process, weight is adjusted in such a manner so that the difference between the desired input and the actual output is minimum.

ii. Unsupervised learning

In this learning process, the desired response is unknown, so error information cannot be used to improve network behavior. Since there is no information on the correctness or inaccuracy of the response, learning can be accomplished based on observations of reactions to our marginal or ignorant inputs.

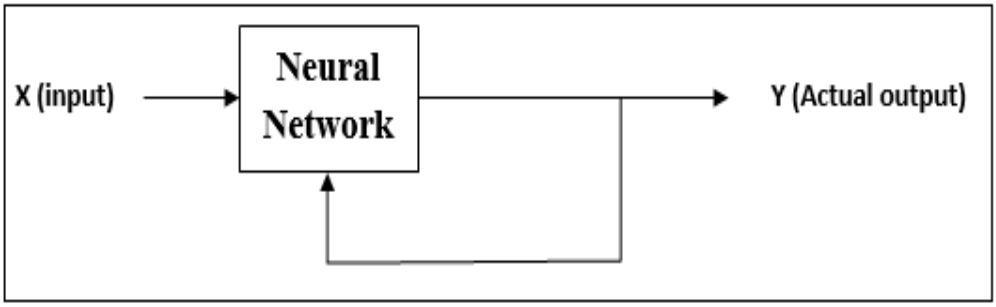


Figure 9. Unsupervised learning

As shown in the figure above, in unsupervised learning process no feedback algorithm is used. Hence in this system, the neuron itself find the pattern and characteristics from the i/p data and the relationship among the i/p and o/p data.

7. Conclusions

Due to the typical filtering along with delay comprising operations of most receivers, an offset will be there witha receivednumber of bitsand transmitted ones. Prior comparison of sequences of two bits to investigate for errors, firstly determine this offset. Once it's done

then offset connecting the bit vectors for sending and receiving, thencalculates the bit error. For bit errors, the bit value will only be in a position where the value in the error vector is non-zero. Run the simulation each time to calculate the bit error rate; send and gathers a fixed bit in different SNR scenarios.

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